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Image Compression Using DPCM Quantization

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Abstract: Image processing modifies pictures to improve, extract information, and change their structure (composition, image editing, image compression, etc.). Images can be processed by optical, photographic, and electronic means, but image processing using digital computers is the most common method due to its speed, flexibility, and precision. Compression involves reducing redundancy in the image data to optimize transmission and storage. Differential Pulse Code Modulation (DPCM) is a method that uses prediction and quantization techniques to efficiently compress images by removing unused bits. In this paper, we evaluate the results of image compression using 3-bit DPCM quantization, analysing the in this study quality through histograms, prediction mean square error, and distortion levels. The results demonstrate that DPCM with 3-bit quantization achieves a good balance between image reconstruction and file size reduction, providing a clear trade-off between compression ratio and image quality. This paper explores the effects of 3-bit quantization on image compression, focusing on prediction accuracy and distortion.

Keywords: Image Compression, Quantization, Prediction Error, Image Processing.

I. INTRODUCTION

In modern image processing, one of the most crucial tasks is image compression, which allows for significant reductions in file sizes while retaining as much visual information as possible. This is especially important for storage and transmission in applications such as digital media, satellite imagery, and medical imaging. One of the most effective techniques for image compression is Differential Pulse Code Modulation (DPCM), which reduces redundancy by predicting pixel values based on their neighbours and encoding the difference (error). The error values are then quantized to compress the image [1], [2]. An image is composed of a grid of pixels arranged in rows and columns, where each pixel represents the intensity or colour information at a specific location in the image matrix as illustrated in Figure 1.

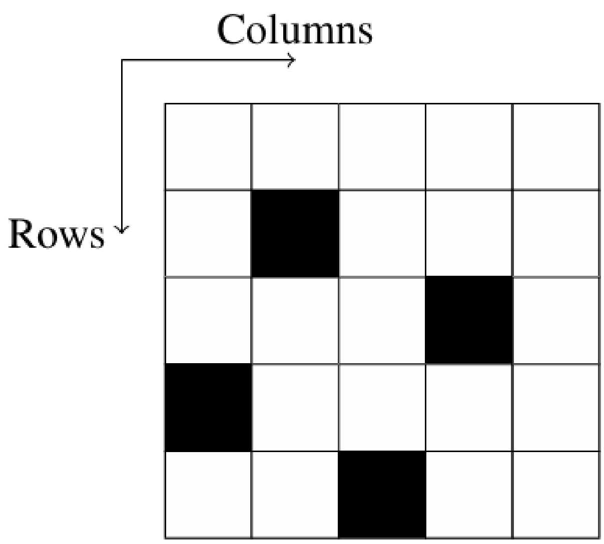

Figure 1. Illustration of an image as a grid of pixels arranged in rows and columns

In this study [3] , we focus on 3-bit quantization in DPCM for image compression. 3-bit quantization allows for 8 distinct quantization levels, providing a balance between compression and image quality. The study evaluates how the 3-bit quantization affects the Prediction Mean Squared Error (MSE), Peak Signal-to-Noise Ratio (PSNR), and the compression ratio. Additionally, adjusting the dynamic range of the error quantizer significantly influences the accuracy of

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reconstruction — a narrower range may cause clipping of large prediction errors, while a wider range reduces quantization resolution and increases distortion.

II. DPCM METHODOLOGY AND SYSTEM OVERVIEW

The image compression process in this study follows the Differential Pulse Code Modulation (DPCM) pipeline [4]: prediction, error calculation, quantization, reconstruction, and encoding/decoding. Unlike traditional raster scanning, this implementation processes the image diagonally—first the upper triangle of the matrix (including the main diagonal), followed by the lower triangle. This ensures that necessary neighbouring pixels are available during prediction. The encoder and decoder architecture is shown in Fig. 2.

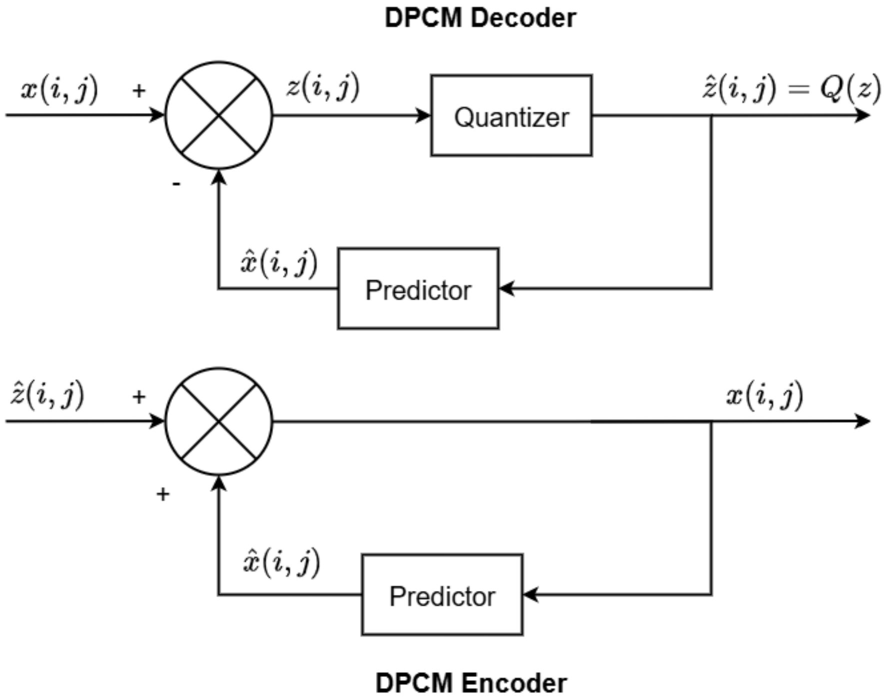

Figure 2. DPCM Encoder and Decoder Block Diagram

A. DPCM Encoder Process

Prediction: The predicted value $\hat{x}(i,j)$ of a pixel is based on the location of the pixel in the matrix. For the top-left pixel (1, 1), the prediction is initialized to zero. For pixels along the f irst row or column, prediction uses only one neighbor. For all other pixels, the prediction is computed as the average of the left and top neighbours:

$$\hat{x}(i,j) = \begin{cases} 0, & if\ i = 1, j = 1 \\ 0.5 * x\ (i, j-1), & if\ i = 1, j > 1 \\ 0.5 * x\ (i-1, j), & if\ i > 1, j = 1 \\ 0.5 * x\ (i-1, j) + 0.5 * x\ (i, j-1)\ , & otherwise \end{cases} \qquad \text{---Eq (1)}$$

Prediction Error: The error is computed as the difference between the original pixel value and its predicted value:

$$z(i,j) = x(i,j) - \hat{x}(i,j) \qquad \text{---Eq (2)}$$

Quantization: The error is then quantized using a uniform quantizer. In this implementation, a 3-bit quantizer is used to reduce bit depth:

$$Q(i,j) = Q(z(i,j)) \qquad \text{---Eq (3)}$$

Encoding: The quantized error $Q(i,j)$ is converted to binary form for storage or transmission.

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B. DPCM Decoder Process

Decoding: The binary stream is decoded back into quantized prediction errors:

$$\hat{z}(i,j) = Q(i,j) \quad \text{---Eq (4)}$$

Prediction: The predicted value $\widehat{x_{pred}}(i,j)$ of a pixel is based on the location in the matrix, where $\widehat{x_{pred}}(i,j)$ is the same predictor used during encoding, based on already reconstructed pixels. For the top-left pixel (1,1), the prediction is initialized to zero. For pixels along the first row or column, prediction uses only one neighbour. For all other pixels, it uses both top and left neighbours:

$$\widehat{x_{pred}}(i,j) = \begin{cases} 0, & if\ i = 1, j = 1 \\ 0.5 * x(i, j-1), & if\ i = 1, j > 1 \\ 0.5 * x\ (i-1, j), & if\ i > 1, j = 1 \\ 0.5 * \hat{x}\ (i-1, j) + 0.5 * x\ (i, j-1), & otherwise \end{cases} \quad \text{---Eq (5)}$$

Reconstruction: Each pixel is reconstructed by adding the decoded quantized error to the predicted value:

$$x(i,j) = \widehat{x_{pred}}(i,j) + \hat{z}\,(i,j) \quad \text{--- Eq (6)}$$

III. RESULTS AND DISCUSSION

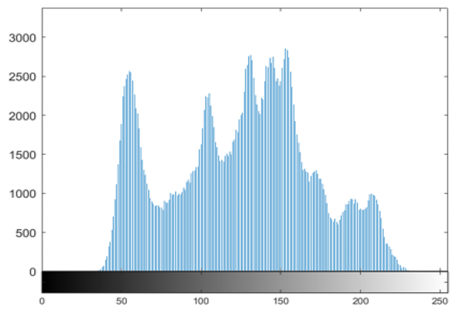
After applying 3-bit quantization within the DPCM compression framework, several qualitative and quantitative results were observed and analysed to assess the impact on image fidelity and data efficiency.

A. Original Image

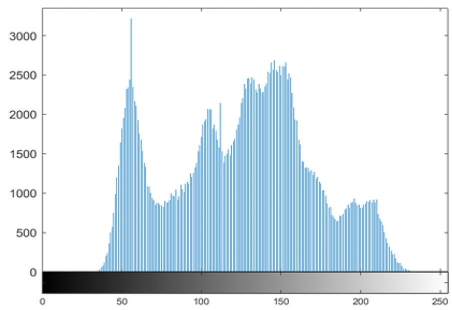
The original image is a standard grayscale image of resolution 512x512 pixels. It serves as the reference point for visual and statistical comparison. in this study, The reconstructed image was obtained after applying DPCM encoding and decoding using 3-bit quantization. While the general structure and features of the original image are preserved, fine details are slightly smoothed out due to quantization loss. Despite this, the visual quality remains acceptable for many practical applications such as preview or archival use.

B. Histogram Comparison

The histogram of the original image displays a broad and continuous distribution of Gray levels, indicating a rich range of tonal values. In contrast, the histogram of the compressed image reveals a more discrete and clustered distribution, reflecting the limited set of quantization levels (only 8 values for 3-bit quantization). This reduction leads to banding artifacts and a loss of subtle intensity variations, which is typical in aggressive quantization (See Fig.3).



(a) Original Histogram



(b) Compressed Histogram

Figure 3. Histogram Comparison: Before and After Compression

C. Prediction Error Distribution

The histogram of the prediction error—i.e., the difference between the actual pixel value and its predicted value—shows a distribution that is sharply cantered around zero (see Fig. 4). This reflects the effectiveness of the predictor in estimating

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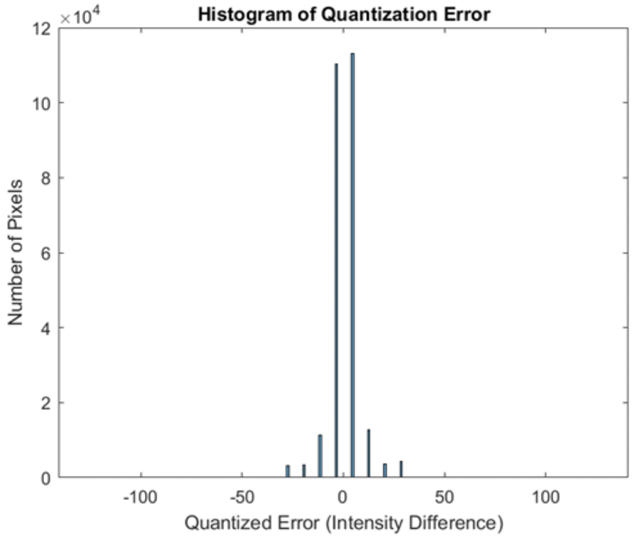

Figure 4. Histogram of Prediction Error Values

pixel values based on their spatial neighbours. Most prediction errors fall within a narrow range around zero, indicating high prediction accuracy, while larger errors are relatively infrequent. This concentrated distribution is highly beneficial for quantization, as it allows a small number of bits to represent most error values with minimal distortion.

D. **Quantization Error**

Quantization error is the difference between the original prediction error $z(i,j)$ and its quantized version $\hat{z}(i,j)$, defined as:

$$e_q(i,j) = z(i,j) - \hat{z}(i,j) \text{ --- Eq (7)}$$

This error represents the distortion introduced by the quantization process, which reduces the continuous range of prediction error values to a finite set of discrete levels. In this project, using 3-bit quantization results in 8 levels, causing some information loss. The quantization error typically appears as subtle variations across the image, depending on the local prediction characteristics. Figure 5 shows the quantization error image, where each pixel represents the difference between the original and quantized prediction error values. The image reveals that the quantization error remains relatively small and does not introduce significant visual artifacts. This error represents the distortion introduced by the quantization process, which reduces the continuous range of prediction error values to a finite set of discrete levels. In this project, using 3-bit quantization results in 8 levels, causing some information loss. The quantization error typically appears as subtle variations across the image, depending on the local prediction characteristics. Figure 5 shows the quantization error image, where each pixel represents the difference between the original and quantized prediction error values. The image reveals that the quantization error remains relatively small and does not introduce significant visual artifacts.

Fig. 5: Quantization error image: showing the difference between original and quantized prediction errors

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To analyse the impact of different quantization ranges on er ror statistics, Table I presents the mean and standard deviation of the prediction error under three different dynamic ranges using 3-bit quantization: [−16,16], [−32,32], and [−64,64]. These ranges represent increasing flexibility in capturing larger error values, at the cost of reduced quantization precision.

TABLE I PREDICTION ERROR STATISTICS FOR DIFFERENT QUANTIZATION RANGES (3-BIT)

Dynamic Range	Mean Error	Standard Deviation
[-16,16]	0.2423	5.9599
[-32,32]	0.2428	7.7250
[-64,64]	0.2430	10.5149

(a) Original Image (b) Compressed Image

Fig. 6: Visual Comparison: Original vs. Compressed Image.

The results demonstrate that DPCM with 3-bit quantization can achieve a significant compression ratio (approximately 3:1) while maintaining reasonable image quality. This is suitable for scenarios where bandwidth or storage is limited, and some loss of fidelity is acceptable. However, the limited quantization depth introduces visual artifacts such as blockiness and intensity banding, particularly in areas with smooth gradients. From the histogram analysis, it's clear that much of the image detail is sacrificed, as reflected in the clustered pixel intensity values.
Nevertheless, the overall structure of the image remains recognizable, showing the strength of predictive coding in preserving dominant features. For applications requiring higher fidelity, using 4-bit or 5-bit quantization might be more appropriate, offering a better trade-off between compression efficiency and visual quality. Further improvements could be explored by combining DPCM with entropy coding techniques like Huffman or arithmetic coding.

IV. COMPRESSION PERFORMANCE EVALUATION

A. **Quantization Parameters Compression**

The compression performance of the DPCM system using 3-bit quantization is summarized in Table II. The metrics include Mean Squared Error (MSE) and Peak Signal-to-Noise Ratio (PSNR), each computed after image reconstruction to evaluate the effectiveness of the compression. Additionally, the effect of varying the dynamic range of the quantizer is presented to observe its influence on distortion levels and reconstruction quality.

TABLE II COMPRESSION PERFORMANCE METRICS FOR 3-BIT DPCM WITH VARYING DYNAMIC RANGES

Dynamic Range	MSE	PSNR [dB]
[-16,16]	127.6098	27.0720
[-32,32]	37.8854	33.3461
[-64,64]	27.1009	33.8010

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As shown, increasing the dynamic range improves MSE and PSNR, since it allows the quantizer to better represent larger prediction errors. However, the improvement diminishes at higher ranges, indicating a trade-off between dynamic range coverage and quantization precision. The mathematical formulas for each metric are provided below:

$$MSE = \frac{1}{N}\sum_{n=1}^{N}\left(x(n) - \hat{x}(n)\right)^2 \quad \text{--- Eq (8)}$$

$$PSNR = 10\log_{10}\left(\frac{Max_{value}^2}{MSE}\right) \quad \text{--- Eq (9)}$$

$$CR = \frac{Bit\ Depth}{DPCM\ Compression} = \frac{8}{3} \approx 2.667\ Bits \quad \text{--- Eq (10)}$$

Below is a brief explanation of each metric used:

Mean Squared Error (MSE): Measures the average squared difference between the original pixel values x(n) and recon structed values $\hat{x}(n)$. A lower MSE (see Eq. 8) indicates better reconstruction quality.

Peak Signal-to-Noise Ratio (PSNR): Expressed in decibels (dB), PSNR is a logarithmic metric that reflects the quality of the reconstructed image. A higher PSNR (see Eq. 9) indicates less distortion and higher fidelity.

Compression Ratio (CR): Represents the ratio between the original and compressed image sizes. The original image size $Soriginal$ is calculated as:

$$S_{original} = 512X512X8 = 2{,}097{,}152\ bits = 262\ KB \quad \text{--- Eq (11)}$$

The compressed image size $S_{compressed}$ using 3-bit quantization is:

$$S_{compressed} = 512X512X3 = 786{,}432\ bits = 98\ KB \quad \text{--- Eq (12)}$$

The theoretical compression ratio CR is given by:

$$CR = \frac{S_{original}}{S_{compressed}} = \frac{2{,}097{,}152}{786{,}432} \approx 2.67{:}1 \quad \text{--- Eq (13)}$$

The actual compression ratio achieved in the system is approximately 3:1, reflecting encoding overheads and optimizations beyond simple bit-depth reduction.

B. Comparison of Quantization Bit-depths

To further evaluate the impact of quantization resolution, a comparison was performed using 1-bit, 3-bit, and 4-bit quantizers over the full dynamic range [−255,255]. Table III summarizes the results in terms of Mean Squared Error (MSE) and Peak Signal-to-Noise Ratio (PSNR).

TABLE III PERFORMANCE COMPARISON FOR DIFFERENT QUANTIZATION BIT-DEPTHS OVER FULL RANGE [−255,255]

Quantization Bits	MSE	PSNR [dB]
1 - Bit	5156.029	11.007
3 - Bit	361.647	22.548
4 – Bit	94.190	28.390

As expected, increasing the number of quantization bits significantly reduces the distortion in the reconstructed image. A 1-bit quantizer introduces substantial error, leading to a low PSNR. In contrast, 4-bit quantization achieves high fidelity with minimal distortion, balancing compression and quality effectively.

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Fig. 7: Reconstructed Images using 1-bit, 3-bit, and 4-bit Quantization (Left To Right).

V. CONCLUSION

This study demonstrates the effectiveness of 3-bit DPCM (Differential Pulse Code Modulation) quantization for grayscale image compression. The results show that this predictive coding method can significantly reduce file size while maintaining an acceptable level of image quality, as reflected in the computed PSNR and MSE values. The reconstructed image retains the overall structure and recognizable features of the original, despite the lossy nature of the compression. By leveraging spatial redundancy in the image, DPCM efficiently predicts pixel values based on neighbouring pixels, allowing the system to encode only the prediction error. When combined with scalar quantization (in this case, 3 bit), the overall data rate is greatly reduced. The histogram analysis of the prediction error confirms that the error values are predominantly cantered around zero, which is ideal for quantization and helps minimize perceptual distortion. Furthermore, an investigation of different dynamic ranges for quantization reveals a trade-off between quantization precision and range coverage. As the dynamic range increases, both MSE and PSNR improve, though with diminishing returns. This highlights the importance of selecting an optimal dynamic range that balances performance and complexity, especially in resource-constrained systems such as embedded or real-time applications. Overall, 3-bit DPCM offers a compelling combination of low complexity, moderate compression, and acceptable reconstruction quality. It is particularly suited for applications where simplicity and bandwidth savings are more critical than perfect visual fidelity such as preview systems, archival storage, or transmission over limited-bandwidth channels. Future work could explore adaptive quantization, context-aware predictors, or hybrid techniques to further enhance performance while maintaining low computational cost.

REFERENCES

[1]. R. C. Gonzalez and R. E. Woods, Digital Image Processing, 4th ed., Pearson, 2018.
[2]. K. Sayood, Introduction to Data Compression, 5th ed., Morgan Kaufmann, 2017.
[3]. A. K. Jain, Image Data Compression: A Review, Proceedings of the IEEE, vol. 69, no. 3, pp. 349–389, Mar. 1981.
[4] J. W. Woods, Subband Coding for Image Compression, IEEE Transactions on Acoustics, Speech, and Signal Processing, vol. 38, no. 5, pp. 995–1001, May 1990.

